Project Report: AAPL Close Price Prediction using LSTM

By: Abhishek Patil

1. Introduction:

The aim of this project is to forecast the closing prices of AAPL stock utilizing the Long Short-Term Memory (LSTM) model, a specialized type of recurrent neural network (RNN) renowned for its proficiency in analyzing sequential data. This report offers a detailed overview of the methodology, execution, and assessment of the LSTM model for predicting AAPL stock prices.

2. Data Collection and Preprocessing:

Data Source: Daily historical data of AAPL stock from 2010 to 2024 retrieved from Yahoo Finance.

Preprocessing Steps:

- **Data Scaling:** Normalizing the data to ensure uniform scaling across all features.

3. LSTM Model Development:

Architecture:

- A Sequential Model comprising two LSTM layers succeeded by Dense layers.

LSTM Parameters: Determining the number of units, activation functions, and dropout rates.

Compilation:

Selection of optimizer: Adam

Loss Function: Mean Squared Error

Training:

- Segregation of data into training and validation sets.
- Training the model on historical data.

Model Evaluation:

Performance Metrics: Evaluation based on R-Squared, Mean Squared Error, and Root Mean Squared Error.

Visualizations: Creation of line plots depicting actual vs. predicted closing prices, along with error plots to highlight any disparities.

4. Theoretical Understanding of LSTM:

Sequential Data Handling:

Financial data, such as stock prices, is inherently sequential, where each data point is contingent on preceding ones. LSTM is adept at discerning patterns and dependencies within such sequential data.

Memory and Forget Gates:

Key to LSTM's functionality are mechanisms like memory cells and gates, which enable it to retain pertinent information over extended periods while selectively discarding irrelevant data.

Update and Output Gates:

LSTM employs update and output gates to manage the flow of information within the memory cell, thereby determining the relevance and utility of stored information.

Training and Learning:

During the training phase, the LSTM model adjusts its parameters based on historical data through backpropagation, a process wherein errors are propagated backward through the network to fine-tune the parameters.

5. Results and Analysis:

Performance Metrics:

- **R-Squared:** 93.17%
- **Mean Squared Error:** 25.12
- **Root Mean Squared Error:** 5.01

Visualizations:

Line plots illustrating the correspondence between actual and predicted closing prices, alongside error plots highlighting any deviations.

Analysis:

The LSTM model exhibits robust predictive capabilities, effectively capturing underlying patterns within AAPL stock prices.

6. Future Directions:

- **Backtesting:** Further validation to ascertain the model's robustness and detect any instances of overfitting.
- **Model Enhancement:** Fine-tuning LSTM parameters, exploring alternative architectures to optimize performance.
- **Extension:** Expanding the model's scope to encompass the prediction of stock prices for other companies.
- **Deployment**: Integrating the model into trading algorithms for real-time forecasting and decision-making.

7. Conclusion:

The LSTM model developed in this project offers promising insights into forecasting AAPL stock prices. With ongoing refinement and validation, it holds the potential to serve as a valuable asset for financial analysts and traders in making well-informed decisions.

8. References:

- **Data Source:** Yahoo Finance
- **Libraries:** Pandas, Scikit-learn, Keras
- **Tools:** Python

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Project Background:

we are trying to predict the close prices of AAPL stock using LSTM model. We have gathered the daily data of APPLE STOCK from 2010 to 2024 apple stock.

Importing all the required Libraries:

```
import math
import yfinance as yf
import pandas_datareader as web
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, LSTM
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
from sklearn.metrics import r2_score, mean_squared_error
```

Download the Required Data from Yahoo Finance:

```
# Download AAPL data from 2010-01-01 to 2024-01-01
aapl_data = yf.download('AAPL', start='2010-01-01', end='2024-01-01')

# Print the last few rows of the data
aapl_data.tail()
```

```
[*********************100%%**********************]  1 of 1 completed
```

Date	Open	High	Low	Close	Adj Close	Volume
2023-12-22	195.179993	195.410004	192.970001	193.600006	193.353287	37122800
2023-12-26	193.610001	193.889999	192.830002	193.050003	192.803986	28919300
2023-12-27	192.490005	193.500000	191.089996	193.149994	192.903839	48087700
2023-12-28	194.139999	194.660004	193.169998	193.580002	193.333298	34049900
2023-12-29	193.899994	194.399994	191.729996	192.529999	192.284637	42628800

```
aapl_data.shape
```

```
(3522, 6)
```

```
#Visualize the closing price history
plt.figure(figsize = (16,8))
plt.title('Close Price History')
plt.plot(aapl_data["Close"])
plt.xlabel('Date', fontsize = 18)
plt.ylabel('Price of AAPL', fontsize = 18)
plt.show()
```


```
#Create a mew dataframe
aapl_close_data = aapl_data.filter(['Close'])

#Convert the DataFrame to a numpy array
dataset = aapl_close_data.values

# Get the numbe of rows to train the model on
training_data_len = math.ceil(len(dataset) * 0.8)
```

```
# Scale the data
scaler = MinMaxScaler(feature_range=(0,1))

scaled_data = scaler.fit_transform(dataset)


# Create teh training data
# Create the scaled training data set

train_data = scaled_data[0:training_data_len,:]

#Split the data into x_train and y_train datasets
x_train = []
y_train = []

for i in range(60, len(train_data)):
  x_train.append(train_data[i-60:i,0])
  y_train.append(train_data[i,0])
  if i <=60:
    print(x_train)
    print(y_train)
    print()
```

```
[array([4.10081399e-03, 4.16990948e-03, 3.53312539e-03, 3.46029250e-03,
       3.72172994e-03, 3.37253003e-03, 2.92621544e-03, 3.47336463e-03,
       3.24554370e-03, 2.59195259e-03, 4.29315593e-03, 3.67504878e-03,
       2.99157355e-03, 1.06441674e-03, 2.05787553e-03, 2.59382004e-03,
       2.95609707e-03, 1.35199593e-03, 1.86495266e-06, 5.00460545e-04,
       7.11476946e-04, 1.34079126e-03, 0.00000000e+00, 6.36779110e-04,
       3.86548837e-04, 7.73102661e-04, 5.73288442e-04, 1.23621678e-03,
       1.55554505e-03, 2.11950124e-03, 1.96077333e-03, 2.03173129e-03,
       1.79643809e-03, 1.56301234e-03, 9.35565469e-04, 1.60783353e-03,
       1.85806380e-03, 2.34732217e-03, 3.16338107e-03, 3.13723683e-03,
       3.22686675e-03, 3.48456930e-03, 5.02331232e-03, 5.04758912e-03,
       5.78334535e-03, 6.12321054e-03, 6.24645698e-03, 6.45187603e-03,
       5.93647342e-03, 6.05038264e-03, 5.98875942e-03, 6.08773156e-03,
       5.63955451e-03, 6.10640602e-03, 6.78053654e-03, 6.96914608e-03,
       6.46121077e-03, 7.25486281e-03, 7.53309979e-03, 8.17922111e-03])]
[0.008020490703601182]
```

```
# Convert the x_train and y_train to numpy arrays
x_train, y_train = np.array(x_train), np.array(y_train)
x_train.shape
```

```
(2758, 60)
```

```
#Reshape the data
x_train = np.reshape(x_train,(x_train.shape[0],x_train.shape[1],1))
x_train.shape
```

```
(2758, 60, 1)
```

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture that is particularly effective for sequential data like time series, making it suitable for financial data analysis and stock price prediction.

Here's a simplified explanation of how LSTM works in finance:

1) Sequential Data Handling: In finance, historical stock price data is sequential, where each data point depends on previous ones. LSTM is well-suited for capturing patterns and dependencies in such sequential data.

2) Memory and Forget Gates: LSTM has the ability to retain information over long periods and selectively forget irrelevant information. It achieves this through mechanisms called memory cells and gates.

Memory Cell: The memory cell stores information over time.

Forget Gate: This gate decides which information to discard from the cell state.

3) Update and Output Gates: LSTM also has mechanisms for updating and outputting information from the memory cell.

Update Gate: This gate decides how much of the new information will be stored in the memory cell.

Output Gate: It controls how much information from the memory cell will be used to predict the output.

4) Training and Learning: During training, the LSTM model adjusts its parameters (weights and biases) based on historical data to learn patterns and relationships. It does this through a process called backpropagation, where errors are propagated backward through the network to update the parameters.

Example:

Let's say we want to predict the closing price of a stock based on its historical prices over the past 30 days. We can use an LSTM model to learn patterns from this historical data and make predictions for future closing prices.

1)Input Data: For each day, we input the stock's closing price, volume, and other relevant features over the past 30 days.

2)LSTM Model: The LSTM model processes this sequential input data, learning patterns and relationships between past prices and future prices.

3)Training: During training, the model adjusts its parameters by comparing its predictions with actual closing prices from the training data.

4)Prediction: After training, the model can predict the closing price for the next day based on the most recent historical data.

In summary, LSTM models in finance analyze sequential data like historical stock prices, capturing patterns and dependencies to make predictions about future prices. They are trained to remember relevant information while discarding irrelevant data, enabling accurate forecasting of stock prices.

```
# Build the LSTM Model
model = Sequential()
model.add(LSTM(50, return_sequences = True, input_shape = (x_train.shape[1],1)))
model.add(LSTM(50, return_sequences = False))
model.add(Dense(25))
model.add(Dense(1))


# Compile the model
model.compile(optimizer = 'adam', loss = 'mean_squared_error')


# Train the model
model.fit(x_train, y_train, batch_size=1, epochs = 1)
```

```
2758/2758 [==============================] - 100s 35ms/step - loss: 5.1453e-04
<keras.src.callbacks.History at 0x7c1db53d7220>
```

```
# Create the testing dataset
# Create a new array containing scaled values from index 2758 to 3522
test_data = scaled_data[training_data_len-60: , :]

# Create the datasets x_test and y_test
x_test = []
y_test = dataset[training_data_len:,:]

for i in range(60, len(test_data)):
  x_test.append(test_data[i-60:i,0])


# Convert the data to a numpy array
x_test = np.array(x_test)


# Reshape the data
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1],1))



# get the models predicted values
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)
```

```
22/22 [==============================] - 1s 18ms/step
```

```
r_squared = r2_score(y_test, predictions)
mse = mean_squared_error(y_test, predictions)
rmse = np.sqrt(mse)

print(r_squared)
print(mse)
print(rmse)
```

```
0.9317281152030685
25.12545287190592
5.012529588132715
```

Performance Metrics:

R-Squared: 93.17 %

Mean Squared Error: 25.12

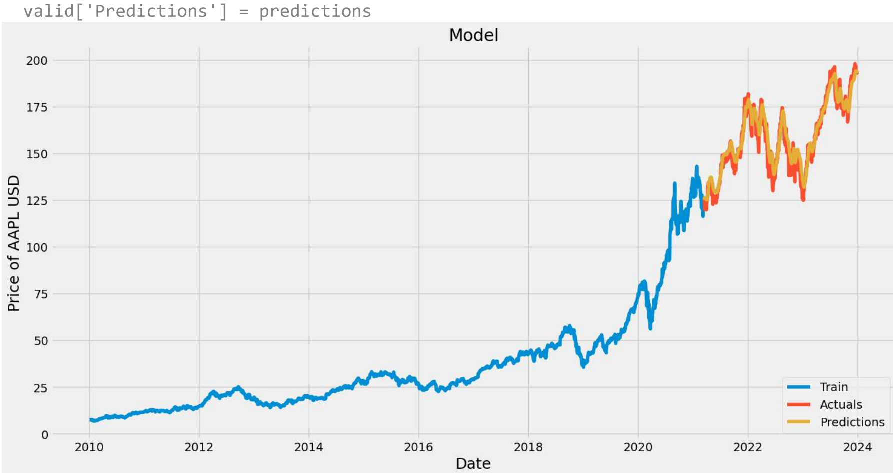
Root Mean Squared Error: 5.01

These metric are realtively good for the LSTM model.

```
# Plot the data
train = aapl_data[:training_data_len]
valid = aapl_data[training_data_len:]
valid['Predictions'] = predictions
# Visualize the data
plt.figure(figsize = (16,8))
plt.title('Model')
plt.xlabel('Date', fontsize = 18)
plt.ylabel('Price of AAPL USD', fontsize = 18)
plt.plot(train['Close'])
plt.plot(valid[['Close', 'Predictions']])
plt.legend(['Train', 'Actuals', 'Predictions'], loc = 'lower right')
plt.show()
```

```
<ipython-input-47-fe342363abb7>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
  valid['Predictions'] = predictions
```



```
valid[["Close", "Predictions"]]
```

Date	Close	Predictions
2021-03-16	125.570000	123.698273
2021-03-17	124.760002	124.235130
2021-03-18	120.529999	124.669403
2021-03-19	119.989998	124.481834
2021-03-22	123.389999	124.049240
...	...	...
2023-12-22	193.600006	184.247253
2023-12-26	193.050003	183.985336
2023-12-27	193.149994	183.687149
2023-12-28	193.580002	183.449890
2023-12-29	192.529999	183.325150

704 rows × 2 columns

Predicting the next days Price:

```
# Get the quote
# Download AAPL data from 2010-01-01 to 2024-01-01
aapl_data = yf.download('AAPL', start='2010-01-01', end='2024-01-01')

#Create a New DataFrame
new_df = aapl_data.filter(["Close"])

#Get the last 60 days Closing Prices
last_60_days = new_df[-60:].values

#Scale the data to be the values between 0 an 1
last_60_days_scaled = scaler.transform(last_60_days)

#Create an empty list
X_test = []
X_test.append(last_60_days_scaled)

#Convert the x_test datates to numpy array
X_test = np.array(X_test)

# Reahape the data
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))

# Get the predicted Scaled Prices
pred_price = model.predict(X_test)

#Undo the Scaling
pred_price = scaler.inverse_transform(pred_price)

print(pred_price)
```

```
[*********************100%%**********************]  1 of 1 completed
1/1 [==============================] - 1s 850ms/step
[[183.1317]]
```

Future Application:

1) we have used LSTM model beacuse of which it is really hard to backtest this model.

2) The performance metrics are way too good so we need to check for overfitting that's why backtesting the model is necessary.

3) we can use this model to predict the stock price of different Stocks as well.

Start coding or generate with AI.